Title
Additionality Effects of Rebate Programs in the Residential Water Sector: Indoor vs. Outdoor

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Abstract

Rebate programs are often used in the residential water sector to alleviate market failures that may hamper the adoption of water-efficient technologies. In this paper, we examine whether several rebate programs stimulate or crowd out private investment in indoor and outdoor technologies. To do so, we use a panel of household-level data from a water district in Southern California for the period 2014-2015. Our results indicate that, while all the rebate programs considered in the analysis increase private investment in water-efficient technologies, only outdoor rebate programs generate further private investment in other outdoor technologies.

JEL-Classification: Q20; Q25; Q28.

Keywords: Residential Water Demand; Rebate Programs; Additionality; Average Treatment Effect

1 Introduction

As more frequent and severe droughts are expected to affect many parts of the world, increasing efforts are being made to ensure water availability. Innovation in water-efficient technologies (such as low-flow toilets, high-efficiency washing machines and weather-based irrigation controllers) has rapidly increased in recent years, as can be inferred from the rise in the number of patents in this sector. The number of patents granted worldwide for demand-side (i.e. water conservation) technologies has increased by 150.3% from 2005 to 2014, whereas the total number of patents worldwide increased by only 102.14% during the same period(OECD, 2017).

However, the increase in the number of patents alone is not sufficient to generate water savings from a new technology. As noted by Jaffe and Stavins (1995), water savings result from a three step process. First, a new technical idea needs to be developed (invention); then, this idea needs to be transformed into a product (innovation); last, the product must become widely adopted (diffusion). Similar to the case of environmental pollution studied by Jaffe et al. (2005), there exist market failures associated with water use that interact with market failures related to technological innovation and diffusion that may hamper the adoption of new technologies. Regarding the former, consider that most water is not supplied by a competitive market, thus consumers do not face the full opportunity cost of their water use. Instead, they typically face the out-of-pocket cost of delivering water. This means water is under-priced, water-efficient technologies are uneconomical compared to their less-efficient alternatives, and thus consumption is inefficiently high. Practical impacts of this include over-extraction of ground and surface water supplies and associated environmental degradation. Regarding the latter type of market failure, consider that innovation and diffusion of new technologies are characterized by uncertainty Jaffe et al. (2005). Greater uncertainty about new technologies compared to their more established alternatives creates a disincentive for adoption, even if consumers would be better-off selecting the new technology. In this context, public policies such as rebate programs (i.e. technology subsidies for consumers) are commonly used to foster the adoption of new water-efficient technologies.

One of the main concerns regarding the use of rebates to promote technology adoption is whether such incentives lead to additional technological adoption that would not have been achieved in the absence of the rebate program. This is known in the literature as the "additionality" question. As Joskow and Marron (1992) argue for the case of electricity conservation programs, many participants in rebate programs may be non-additional, instead obtaining a rebate (subsidy) merely to substitute public funding for private investment in the subsidized technology. As a consequence, several studies in the energy and water economics literatures examine whether rebate programs effectively promote greater adoption of the subsidized technology. Among these, Boomhower and Davis (2014) use a regression discontinuity analysis to examine additionality of energy-efficiency subsidies, focusing on air conditioners and refrigerators. Bennear et al. (2013) estimate a difference-in-difference model to measure the reduction in water use generated by a rebate program for the adoption of high-efficiency toilets. And Brent et al. (2015) analyze data from three randomized field experiments to understand whether social comparisons act as a water conservation tool, in particular when interacted with rebate programs. While most papers measuring additionality analyze the effect of rebate programs in terms of reductions in energy and water consumption, as far as we are aware, no study considers whether participation in rebate programs may affect private investments in other efficient technologies.

In this paper, we take a different approach to analyze the effectiveness of rebate programs by adapting a common method in the R&D literature. In particular, we compare the level of investment in water-efficient technologies between rebate program participants and non-participants, but we do not limit our focus to the subsidized technology. Rather, we consider the extent to which a rebate for a water efficient technology creates additional private investment in water efficiency more generally. This approach allows us to tackle two research questions. The first is similar to the additionality question but broader: does a technology rebate lead to private investments in water-efficient technologies beyond what would have been achieved in the absence of the rebate program? That is, we test for a "crowding-out" effect. The second question is: does a technology rebate lead to private investment in unsubsidized water-efficient technologies specifically? We refer to this as an "acceleration effect". One of the main advantages of our approach compared to previous papers in the water economics literature is that it allows us to disentangle this indirect investment effect.

To examine these two questions, we use data from the Moulton Niguel Water District in Southern California. These data are particularly useful because multiple rebate programs for the adoption of both indoor and outdoor water-efficient technologies were offered in recent years to strengthen local drought resilience. However, one of the challenges in using this data is that we observe the year but not the month of adoption for the unsubsidized water-efficient technologies. As a consequence, it is not possible to directly measure rebate-induced water savings. Instead, we focus on measuring investment in water-efficient technologies, and use these results combined with water saving estimates from the literature to construct policy implications.

Our results indicate that each of the four rebates considered in the analysis achieve investment in water-efficient technologies that would not have occurred in the absence of the rebate. Moreover, we find that rebates for outdoor water-efficient technologies also achieve additional private investment in other unsubsidized technologies, but rebates for indoor technologies do not. Considering that outdoor technologies also have larger water conservation potential and are generally in earlier adoption stages, policymakers should focus on these technologies to foster water conservation.

2 Motivation for water conservation rebate programs

Water conservation technologies may generate positive externalities (such as enhanced availability of water for environmental or emergency uses, or improved information about the effectiveness of new technologies) that typically are not internalized by the technology adopters. Therefore, the level of privately financed household water conservation may be lower than socially desired, which provides economic motivation for policies that promote greater private investment. In order to encourage greater investment in water conservation technologies, water districts often use rebate programs that reduce the price of these technologies and thus increase demand. However, households may apply for rebate programs merely to finance investment in water conservation technologies that they would adopt anyway in the absence of the incentive. That is, households may substitute public for private investment. On the basis of this reasoning we can hypothesize the following:

Hypothesis 1 (There exists total crowding-out.): *There exists total crowding-out if we observe a complete substitution of public for private investment.*

Under total crowding-out, the level of investment in water-efficient technologies is not significantly larger for households participating in the rebate program. One cause of total crowding-out would be if the average household decides to invest in a certain level of water-efficient technologies separately from the decision participate in the rebate program.

Hypothesis 2 (There exists partial crowding-out.): *Similarly, there exists partial crowding-out when we observe a partial substitution of public for private investment.*

This hypothesis implies that the level of investment in water-efficient technologies among households participating in the rebate program is significantly higher than it would be in the absence of the rebate, but lower than the level of subsidies granted. That is, while there is additional investment in water-efficient technologies, it is less than the amount of rebates offered. In this case, the level of investment in water-efficient technologies excluding the subsidized technology is smaller than the level of investment in water-efficient technologies in the absence of the rebate.

Hypothesis 3 (There is no acceleration effect.): *There is no acceleration when participant households do not adopt other unsubsidized water-efficient technologies jointly with the subsidized technology.*

Under this hypothesis, the rebate program may achieve additional adoption of the subsidized technology, but no further adoption of other water-efficient technologies will be achieved.

3 Method

The hypotheses defined above are tested separately for each of the rebates considered. In order to test these hypotheses, and following Czarnitzki and Hussinger (2004) and Freitas et al. (2017), we first define two measures of investment in technologies for each rebate: the level of investment in water-efficient technologies adopted during the period of observation including the subsidized technology (Tot_WT), and the level of investment in water-efficient technologies adopted during the observation period excluding the subsidized technology ($NoSub\_WT$). To estimate the effect of the rebate programs on these measures, we conduct a treatment analysis that allows us to understand the extent households have adopted water conservation technologies, on average, due to receiving a rebate. We focus explicitly on rebate program participants and we estimate the average treatment effect on the treated (ATET). As noted by Caliendo and Kopeinig (2008), ATET is defined as the difference between the expected outcome (investment in water-efficient technologies) with and without treatment (a rebate) for those participating in the treatment (rebate program participants). Using the measure Tot_WT, ATET is defined as:

$$\tau^{ATET} = E(Tot\_WT_{1i}|R = 1) - E(Tot\_WT_{0i}|R = 1) \tag{1}$$

where τ^{ATET} is the average treatment effect on the treated, and Tot_WT_{1i} and Tot_WT_{0i} indicate the total levels of investment in water conservation technologies in the case of treatment and the counter factual situation of no treatment, respectively. R indicates the treatment status with $R = 1$ indicating that the household receives a rebate.

Similarly, we use the measure $NoSub\_WT$ to estimate another average treatment effect on the treated α^{ATET} defined as:

$$\alpha^{ATET} = E(NoSub\_WT_{1i}|R = 1) - E(NoSub\_WT_{0i}|R = 1) \tag{2}$$

where $NoSub\_WT_{1i}$ and $NoSub\_WT_{0i}$ represent analogous levels of investment for the situations of treatment and no treatment, respectively.

Of course, Tot_WT_{0i} and $NoSub\_WT_{0i}$ are not observed for rebate program participants, as they describe the hypothetical outcomes associated with not receiving a rebate for those households who participated in the rebate program. To address this challenge, we could use non-participants as control group if $E(Tot\_WT_{0i}|R = 1) = E(Tot\_WT_{0i}|R = 0)$ and $E(NoSub\_WT_{0i}|R = 1) = E(NoSub\_WT_{0i}|R = 0)$. However, because rebate participants were not randomly assigned, these conditions likely do not hold, and thus using non-participants as a control group would yield biased results. In order to control for this problem, we follow the approach by Czarnitzki and Hussinger (2004) and Freitas et al. (2017), and implement a matching technique to estimate the average treatment effect on the treated. Matching involves pairing households participating in a rebate program with non-participating comparison households that are similar in terms of observable characteristics. As discussed by Dehejia and Wahba (2002), matching is straightforward if we only observe a small number of characteristics. However, when participant and non-participant households may differ across a large number of variables, matching becomes more difficult.

In this context, propensity score matching can provide a weighting scheme to estimate an unbiased treatment effect. The propensity score, i.e., the probability of receiving a rebate $p(x)$ conditional on some pre-treatment characteristics x is defined as (Becker and Ichino, 2002):

$$p(x) \equiv Pr(R = 1|x) \tag{3}$$

As noted by Dehejia and Wahba (2002), any standard probability model, such as probit, can be used because the objective of the propensity score is to reduce the dimensionality of the observable characteristics, and there are no behavioral assumptions attached to the model. Moreover, Caliendo and Kopeinig (2008) indicate that the choice between logit and probit is not critical, as these models yield similar results. In this paper, the propensity score is estimated using a probit model. Regarding the matching algorithm, we use the nearest-neighbor matching, as it is the most straightforward algorithm (Caliendo and Kopeinig, 2008). This involves matching a household participating in a rebate program with a non-participant household that is closest in terms of its propensity score. When using the nearest-neighbor matching, one has to decide how many non-participant households should be chosen for each household participating in a rebate program. In this paper, we follow the recommendation of Austin (2010) and we select one non-participant household for each participant, as this choice tends to minimize bias.[1]

After matching households based on their propensity score, the second step implies computing the ATET as in Equations (1) and (2):

$$\tau^{ATET} = E(Tot\_WT_{1i}|R = 1, p(x)) - E(Tot\_WT_{0i}|R = 0, p(x)) \tag{4}$$

[1] The reader is referred to (Becker and Ichino, 2002) for more details about the matching algorithm.

$$\alpha^{ATET} = E(NoSub\_WT_{1i}|R = 1, p(x)) - E(NoSub\_WT_{0i}|R = 0, p(x)) \tag{5}$$

And Equation (4) and (5) can be estimated as follows:

$$\tau^{ATET} = \frac{1}{N^T} \sum_{i \epsilon T} \left[Tot\_WT_i^T - \sum_{j \epsilon C(i)} w_{ij} Tot\_WT_j^C \right] \tag{6}$$

$$\alpha^{ATET} = \frac{1}{N^T} \sum_{i \epsilon T} \left[NoSub\_WT_i^T - \sum_{j \epsilon C(i)} w_{ij} NoSub\_WT_j^C \right] \tag{7}$$

where N^T is the number of households participating in a rebate program, $C(i)$ is the set of non-participating households matched to participant household i and w_{ij} is the weight of non-participant household j (with $\sum_{j \epsilon C(i)} w_{ij} = 1$).

Once we obtain τ^{ATET} and α^{ATET}, we can test the hypotheses discussed in Section 2. We can reject the null hypothesis of total crowding-out if we find evidence that $\tau^{ATET} > 0$, i.e., the total level of investment in water-efficient technologies is significantly larger for rebate participants. Moreover, α^{ATET} allows us to simultaneously test Hypothesis 2 and Hypothesis 3. First, if $\alpha^{ATET} \geq 0$, the level of investment in unsubsidized devices among rebate program participants is not less than the level of investment among non-participants, indicating that there is no partial substitution of public for private investment. Therefore, we can reject the null hypothesis of partial crowding-out. Second, if $\alpha^{ATET} > 0$, rebate participants show a larger level of investment in unsubsidized technologies than the level of investment among non-participants. In this case, we can reject the null hypothesis of no acceleration effect.

To further explore the nature of additionality effects, we also disaggregate our data into technologies that are used indoors vs. those that are used outdoors, and consider each subset separately. That is, we conduct the same tests using the investments in indoor and outdoor water-efficient technologies ($Indoor\_WT$ and $Outdoor\_WT$, respectively), and the investments in indoor and outdoor water-efficient technologies excluding the subsidized technology ($IndoorNoSub\_WT$ and $OutdoorNoSub\_WT$).

4 Data

We use a database of single-family residential households in Southern California served by the Moulton Niguel Water District (MNWD). This water district provides water, recycled water and waste-water treatment services to the Orange County cities of Aliso Viejo, Laguna Niguel, Laguna Hills, Mission Viejo, Dana Point and San Juan Capistrano. MNWD is a member agency of Metropolitan Water District of Southern California (MWD), a regional water wholesaler. As such, all households served by MNWD can benefit from the rebate programs offered by MWD. MNWD provided customer records for participation in rebate programs for the adoption of several indoor and outdoor technologies, household water consumption, water prices and household characteristics such as the number of residents and the size of the irrigated area. This information was then merged with data from an online survey about household adoption of a larger set of water-efficient technologies. MNWD customers received an e-mail informing them of the survey and inviting them to participate through the water agency's website. The survey was conducted during fall 2016 and consumers were asked what sort of conservation programs (water-efficient technologies and habits) they adopted (i) within the last year, (ii) between one and two years ago, and (iii) more than two years ago. The total number of respondents who completed the survey was around 4,000, yielding a response rate of around 8.5%.[2] After removing respondent households that did not have complete customer records during the entire reference period in the survey, the resulting database is a panel of 3,343 households for the period fall 2014- fall 2016.

For the first step of the analysis, that is, the estimation of the probability that a household receives a rebate for the adoption of water-efficient technologies, we consider the following four binary indicators as dependent variables:

- *Rebate washers*: a dummy variable that takes value 1 if a household receives a rebate

[2] Selection bias may occur if households equipped with water-efficient technologies are also more likely to respond to the survey. In order to investigate this potential sample selection issue, we computed adoption rates for survey respondents that participated in the rebate programs and compared them with the adoption rates reported by MNWD. Both rates are relatively close and therefore, we can assume that there is not likely a selection issue.

for the adoption of a high-efficiency clothes washer, 0 otherwise.

- *Rebate toilets*: a dummy variable that takes a value 1 if a household receives a rebate for the adoption of a high-efficiency toilet.

- *Rebate landscape*: a dummy variable that takes value 1 if a household participates in the landscape transformation program. This program helps households save water by removing turf and converting to a drought tolerant landscape.

- *Rebate weather controller*: a dummy that takes value 1 if a household receives a rebate for investing in a weather-based irrigation controllers. These controllers automatically adjust the irrigation schedule to account for changing weather.

As explanatory variables for these four regressions, we include a set of socioeconomic and demographic characteristics, indicators of each household's water conservation orientation, variables to account for each household's awareness and previous experience with rebate programs, and each household's self-reported relative importance of factors affecting the decision to adopt water conservation technologies. In terms of socioeconomic and demographic characteristics, we include variables such as the number of residents (*HHS*), the number of children under 6 years old (*Members<6*), the number of children between 6 and 17 years old (*Members6-17*), median income in the relevant census block group (*Income*), the proportion of people within the same census block group who have a bachelors degree (*bachelors*), and the median age of residents in the relevant census block group (*Age*). Moreover, for the two regressions regarding the rebates for outdoor technologies, we also include the amount of irrigated landscape (*Irrigated area*) and a binary indicator that accounts for households in which a gardener controls the irrigation schedule (*Gardener*). Last, we include for the regression regarding the landscape transformation program a dummy variable that takes value 1 if the household belongs to a Home Owners Association (*HOA*), and 0 otherwise. The reason to include this explanatory variable in this regression is that some HOAs have strict regulations about landscapes which may create difficulties or disincentives for participating in the rebate programs. The inclusion of this set of variables is consistent with Alberini et al. (2013), who estimate a probit model to analyze the determinants of receiving rebates or tax credits for the adoption of energy-saving technologies and consider both house and household characteristics as explanatory variables.

Regarding each household's water conservation orientation, we include two categorical indicators of the numbers of water-efficient indoor and outdoor technologies in the previous year (*Indoor technology(t-1)* and *Outdoor technology(t-1)*). Similarly, Allcott et al. (2015) also consider whether households are already equipped with conservation technologies when analyzing the characteristics of energy efficiency subsidy adopters. Moreover, following Beaumais et al. (2010) and Pérez-Urdiales and García-Valiñas (2016), we include a water conservation habits index constructed by calculating the mean score on the survey questions related to the values of water use/conservation habits (possible answers were 1 = yes or 0 = no). We consider only well-established habits that have been performed for at least one year.

In order to account for household awareness and previous experience with rebate programs, we include dummy variables (*Rebate other washers(t-1)*, *Rebate other toilets(t-1)*, *Rebate other landscape(t-1)* and *Rebate other weather controller(t-1)*) that take value 1 if a household has received a rebate in the previous period and 0 otherwise. We also include binary indicators that account for whether the head of the household is aware of the existence of the rebate program[3] (*Rebate aware washers*, *Rebate aware toilets*, *Rebate aware landscape* and *Rebate aware controller*).

Last, we follow Tonn and Berry (1986) and include a set of variables indicating the extent to which respondents self-report that certain incentives are relevant in the decision to adopt water-efficient technologies. In particular, we consider categorical indicators (0-4 scale) for money savings in the water bill (*Money savings*), water savings (*Water savings*), and initial time investment (*Time investment*), duration of the technology adoption project *Duration project* and feedback from friends and neighbors about the technology *Feedback friends*.

[3]For instance, households may receive a rebate without being aware of its existence if they are automatically presented with the discounted price at the store or if their landscapers are making the purchase decision.

Descriptive statistics for the variables included in the propensity score matching step are provided in Table 1.

Table 1: Summary statistics – Propensity Score Matching

	Mean	Std. Dev.	Min	Max	Source
Rebate washers	0.024	0.154	0	1	MNWD records
Rebate toilets	0.036	0.186	0	1	MNWD records
Rebate landscape	0.032	0.175	0	1	MNWD records
Rebate weather controller	0.007	0.086	0	1	MNWD records
Habits	0.527	0.242	0	1	Survey
Rebate other washers(t-1)	0.070	0.255	0	1	MNWD records
Rebate other toilets(t-1)	0.051	0.219	0	1	MNWD records
Rebate other landscape(t-1)	0.072	0.258	0	1	MNWD records
Rebate other weather controller(t-1)	0.087	0.282	0	1	MNWD records
Rebate aware washers	0.515	0.500	0	1	Survey
Rebate aware toilets	0.585	0.493	0	1	Survey
Rebate aware landscape	0.657	0.475	0.	1	Survey
Rebate aware controllers	0.342	0.474	0	1	Survey
HHS	3.939	0.687	3	10	MNWD records
Bachelors	0.489	0.109	0.192	0.723	Census
Income ($1,000)	112.792	33.512	37.161	198.708	Census
Age	43.336	7.166	28.800	62.700	Census
Time investment	2.238	1.229	0	4	Survey
Monetary savings	2.696	1.133	0	4	Survey
Water savings	2.841	1.075	0	4	Survey
Duration project	2.071	1.210	0	4	Survey
Feedback friends	1.736	1.271	0	4	Survey
Members<6	0.170	0.518	0	5	Survey

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Table 1 – continued from previous page

	Mean	Std. Dev.	Min	Max	Source
Members6-17	0.467	0.875	0	9	Survey
Gardener	0.510	0.500	0	1	Survey
HOA	0.737	0.440	0	1	Survey
Irrigated area (1,000 sq ft)	2.811	3.390	0	50.163	MNWD records
Indoor technology(t-1)	2.151	1.149	0	4	Survey
Outdoor technology(t-1)	0.980	1.007	0	4	Survey

For the second step, calculating ATET, we must compare the level of investment in water-efficient technologies between rebate program participants and non-participants. The usual approach in the R&D literature (Czarnitzki and Hussinger, 2004; Freitas et al., 2017) is to use expenditures on new technologies as the variable of interest. However, we do not observe actual expenditures in our data. Instead, we observe only adoption decisions and rebate program participation. Therefore our investment measure is an cardinal index that accounts for the number of water-efficient technologies adopted in each period.[4]

To test for total crowding-out, we consider the total number of water-efficient appliances (Tot_WT), the number of indoor water-efficient appliances ($Indoor\_WT$), and the number of outdoor water-efficient appliances ($Outdoor\_WT$) adopted during the period of observation. To jointly test for partial crowding-out and no acceleration effect, we use $NoSub\_WT$, $IndoorNoSub\_WT$ and $OutdoorNoSub\_WT$. As discussed in Section 3, the difference between these variables and those used to test for total crowding-out is that we exclude the subsidized technology for the rebate program under consideration. For all of these tests, indoor water-efficient technologies include efficient clothes washers, low flow toilets, efficient dishwashers and low flow showers. Outdoor water-efficient technologies include weather-based irrigation controllers, landscape transformation, drip irrigation and pool covers. As can be seen in Table 3, there exist households in our sample that invest in the maximum

[4]While this variable is a proxy for the level of investment in water-efficient technologies, it does not allow us to account for differences in technology quality that could be captured using a monetary indicator.

Table 2: Summary statistics - ATET Estimation

	Mean	Std Dev	Min	Max	N
Tot_WT	0.646	1.009	0	7	6686
NoSub_WT	0.546	0.936	0	7	6686
Indoor_WT	0.300	0.623	0	4	6686
IndoorNoSub_WT	0.240	0.573	0	4	6686
Outdoor_WT	0.346	0.706	0	4	6686
OutdoorNoSub_WT	0.306	0.657	0	4	6686

Table 3: Summary statistics - Treatment Households - ATET Estimation

	Rebate washers		Rebate toilets		Rebate landscape		Rebate weather controller	
	Mean	N	Mean	N	Mean	N	Mean	N
Tot_WT	1.877	162	1.759	241	1.953	211	2.240	50
NoSub_WT	0.648	162	0.589	241	0.820	211	0.980	50
Indoor_WT	1.358	162	1.311	241	0.332	211	0.400	50
IndoorNoSub_WT	0.204	162	0.207	241	0.237	211	0.260	50
Outdoor_WT	0.519	162	0.448	241	1.621	211	1.840	50
OutdoorNoSub_WT	0.444	162	0.382	241	0.583	211	0.720	50

number of indoor or outdoor technologies during the period of analysis, but there is not a household that invests in the maximum level of all technologies.

5 Results and policy implications

5.1 The probability of participating in a rebate program

As explained in Section 3, we start our analysis by estimating the probability of receiving a rebate. In table 4 we report the probit estimation results for each of the rebate programs considered. The estimations reported in Columns (1) and (2) are for indoor water-efficient technologies, i.e., *Rebate washers* and *Rebate toilets*, whereas Columns (3) and (4) show the results for the outdoor water-efficient technologies, that is, *Rebate landscape* and *Rebate weather controller*.

In general, the estimated coefficients, when significant, are intuitive in the four models.

Here, we review some of the most noteworthy results.[5] Comparing the four estimations, we observe, as could be expected, that awareness of each rebate is positive and significant at the 1% level in the four models. That is, this variable is one of the main determinants of rebate participation across different programs. However, previous experience with rebate programs does not have a significant effect in any of the estimations.

Regarding socioeconomic and demographic characteristics, *HHS* has a positive and significant effect (at 5%) on participation in the rebate program for efficient washers and for landscape transformation. That is, the more people living in the household, and presumably more frequent laundry loads, the higher the probability of participating in the rebate program. *Income* has a positive and significant effect (although only at 10%) on *Rebate landscape*, as landscape transformation projects can be expensive even with a rebate. *Age* also has a positive effect on *Rebate landscape* at 1%, whereas the effect is negative and significant on *Rebate weather controller* at 10%. This would be consistent with a desire to save water but aversion to perceived "high-tech" solutions. Moreover, the coefficient of *Members<6* is positive and significant at 5% in the *4th* estimation. This indicates that households with a higher proportion of kids under 6 have a higher probability of receiving a rebate for the adoption of weather-based irrigation controllers, which is a technology that allows them to maintain but efficiently irrigate their lawn.

In terms of the effects of a household's water conservation orientation, we find that households that have previously adopted indoor water-efficient technologies are less likely to participate in indoor rebate programs (the estimated coefficients are significant at the 1% level). For the case of previous outdoor technologies, this effect is also negative and significant at 5% for *Rebate toilets*, but it is positive and significant at 1% for *Rebate weather controller*. The negative effect could mean that these households do not need the support of the rebate program to adopt more water-efficient technologies. Alternatively, households that have already installed water-efficient technologies may be less likely to further invest in new ones—perhaps feeling that they already have achieved adequate efficiency gains. Re-

[5] Given the large number of explanatory variables included in the first step, we have computed the variance inflated factor (VIF) and tolerance value to test for multicollinearity, and we reject it in all cases.

garding the positive effect, one possible explanation is that previous satisfactory experience in conserving water may encourage households to participate in the rebate for weather-based irrigation controllers. The coefficient for *Habits* is negative and significant for the outdoor technology estimations, at the 5% and 1% levels for *Rebate landscape* and *Rebate weather controller*, respectively. Similar to the negative effect of previous technologies on rebate participation, households manifesting water conservation habits may be more likely to invest in these technologies without receiving a rebate, but *Habits* may also be perceived as a substitute for efficient technologies.

Time investment has a positive and significant effect at the 10% level on *Rebate washers*, i.e., households that attach greater importance to the amount of time required to participate in a rebate program are more likely to receive a rebate for efficient washers. Moreover, *Feedback friends* has a positive and significant effect at 5% on *Rebate landscape*, indicating that feedback from friends who have previously transformed their landscape increases the probability of receiving this rebate.

Last, regarding the variables directly linked to the outdoor characteristics, we find that *Gardener* has a negative and significant effect at 5% on *Rebate landscape*, whereas the size of the irrigated area has a positive and significant effect at 5% on this probability. However, neither of these characteristics has a significant effect on *Rebate weather controller*.

Table 4: Estimation results for the probability of receiving a rebate

	Rebate washers	*Rebate toilets*	*Rebate landscape*	*Rebate weather controller*
HHS	0.127**	-0.0395	0.103**	0.121
	(2.55)	(-0.77)	(2.04)	(1.33)
Bachelors	-0.411	0.200	-0.0290	1.052
	(-0.98)	(0.53)	(-0.07)	(1.33)
Income	0.00212	0.00178	0.00219*	-0.000669
	(1.56)	(1.47)	(1.66)	(-0.27)
Age	0.00792	0.00344	0.0155***	-0.0164*
	(1.53)	(0.75)	(3.05)	(-1.74)
Members<6	-0.0328	-0.0353	-0.0809	0.176**
	(-0.46)	(-0.50)	(-1.13)	(2.09)
Members6-17	0.0455	0.00711	0.0104	0.0752

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Table 4 – continued from previous page

	Rebate washers	*Rebate toilets*	*Rebate landscape*	*Rebate weather controller*
	(1.19)	(0.18)	(0.27)	(1.18)
Indoor technology(t-1)	-0.147***	-0.162***	0.0276	0.0149
	(-4.35)	(-5.42)	(0.87)	(0.25)
Outdoor technology(t-1)	0.0136	-0.0887**	-0.0216	0.252***
	(0.36)	(-2.50)	(-0.65)	(4.21)
Time investment	0.0563*	-0.0174	-0.0272	0.0166
	(1.81)	(-0.63)	(-0.83)	(0.27)
Monetary savings	0.0198	-0.0538	0.0574	0.103
	(0.36)	(-1.18)	(1.16)	(1.07)
Water savings	-0.0360	0.0229	0.0229	-0.147
	(-0.63)	(0.48)	(0.44)	(-1.47)
Duration project			-0.0155	-0.0428
			(-0.44)	(-0.60)
Feedback friends			0.0744**	0.0460
			(2.51)	(0.78)
Habits	-0.134	-0.0874	-0.343**	-0.792***
	(-0.87)	(-0.63)	(-2.36)	(-2.92)
Rebate other washers(t-1)	0.153			
	(1.26)			
Rebate other toilets(t-1)		0.0399		
		(0.29)		
Rebate other landscape(t-1)			0.0257	
			(0.22)	
Rebate other weather controller(t-1)				-0.366
				(-1.54)
Rebate aware washers	0.968***			
	(9.49)			
Rebate aware toilets		1.535***		
		(9.44)		
Rebate aware landscape			1.465***	
			(6.67)	
Rebate aware weather controllers				1.561***
				(5.16)
Gardener			-0.144**	0.0367
			(-2.14)	(0.29)
HOA			-0.102	
			(-1.26)	
Irrigated area			0.0209**	0.00429

Continued on next page

Table 4 – continued from previous page

	Rebate washers	*Rebate toilets*	*Rebate landscape*	*Rebate weather controller*
			(2.39)	(0.24)
Constant	-3.324***	-2.799***	-4.535***	-3.783***
	(-9.05)	(-7.87)	(-10.59)	(-5.39)
N	6686	6686	6686	6686

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5.2 Hypothesis testing

As explained in Section 3, we use the propensity scores obtained in the first stage as matching arguments for the second stage. Table 5 reports the second stage estimated average treatment effect on the treated for the variables of interest summarized in Table 3. These estimates represent the average additional numbers of total (*Tot_WT* and *NoSub_WT*), indoor(*Indoor_WT* and *IndoorNoSub_WT*) and outdoor (*Outdoor_WT* and *OutdoorNoSub_WT*) water-efficient technologies adopted by households participating in rebate programs.

First, we consider Hypothesis 1, i.e. total crowding-out. Our results show that τ^{ATET} in Column (1) is positive and significant for each of the four rebates considered. This indicates that all the rebate programs in the analysis generate higher investments in water-efficient technologies, on average, so we can reject Hypothesis 1: total crowding-out. This result remains true when we distinguish between indoor and outdoor water-efficient technologies, as both average treatment effects on the treated for *Indoor_WT* and *Outdoor_WT*, in Columns (3) and (5) respectively, are positive and significant for the four rebates.

However, when we test Hypothesis 2: partial crowding out, and Hypothesis 3: no acceleration, we find mixed results. For indoor rebates, the average treatment effect on the treated for *NoSub_WT*, in Column (2), is negative but not statistically significant. Thus, we reject Hypothesis 2 but we cannot reject Hypothesis 3, i.e., we do not find evidence of partial crowding-out or acceleration. That is, the total number of water-efficient technologies adopted, excluding the technology that was subsidized, is neither higher nor lower for participant households compared to non-participant households. In the case of rebates

Table 5: Average treatment effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Tot_WT	*NoSub_WT*	*Indoor_WT*	*IndoorNoSub_WT*	*Outdoor_WT*	*OutdoorNoSub_WT*
	τ^{ATET}	α^{ATET}	τ^{ATET}	α^{ATET}	τ^{ATET}	α^{ATET}
Rebate washers	1.068***	-0.105	0.914***	-0.216***		
	(8.97)	(-0.96)	(13.09)	(-3.26)		
Rebate toilets	0.971***	-0.129	0.921***	-0.154***		
	(9.06)	(-1.30)	(15.10)	(-2.78)		
Rebate landscape	1.194***	0.171			1.232***	0.194**
	(10.31)	(1.58)			(15.81)	(2.52)
Rebate weather	1.520***	0.420**			1.480***	0.420***
controller	(9.70)	(2.09)			(12.07)	(3.14)

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

for outdoor water-efficient technologies, α^{ATET} is positive, but significant only for *Rebate weather controller* when using *NoSub_WT*, in Column (2), as variable of interest, i.e., we find evidence of acceleration.

When we look at the disaggregated indicators for testing partial crowding-out and no acceleration effect we find a significant negative α^{ATET} when considering *IndoorNoSub_WT*, shown in Column (4). Thus, we cannot reject partial crowding-out or no acceleration for households receiving rebates for indoor water-efficient technologies. This seems to indicate that while, on average, households participating in rebate programs for the adoption of indoor technologies also invest more in outdoor technologies than the control group, their total level of water-efficient technologies adopted during the year excluding the subsidized technology is not significantly higher. However, α^{ATET} is positive and significant for both outdoor rebates when we use *OutdoorNoSub_WT*, in Column (6), indicating that we reject both Hypotheses 2 and 3. That is, households receiving a rebate for landscape transformation or for the investment in weather-based irrigation controllers are more likely to invest in other outdoor water-efficient technologies. These rebates are not only promoting investment in the subsidized technology, but also in other outdoor technologies.

5.3 Policy implications

Our results indicate that rebate programs may have different effects on the level of investment in water-efficient technologies depending on the type of subsidized technology considered. One possible explanation for the differences in rebate effects for indoor and outdoor technologies may be that the subsidized technologies are at different stages of the adoption process. Table 6 shows the percentage of households in our sample that have adopted each technology just prior to our period of analysis. We observe that efficient washers and low flow toilets had already been adopted by around 58% and 61% of our sample, respectively; whereas landscape transformation and weather-based controllers had already been adopted by only 27.07% and 14.92%, respectively.

Table 6: Rates of water-efficient technology adoption prior to the analysis (% of the sample)

	Adoption rates prior to the analysis
Efficient washers	58.42%
Low flow toilets	61.29%
Landscape transformation	27.07%
Weather-based controllers	14.92%

Rogers (2003) states that households adopting a technology after 50% of the population already has adopted, as is the case for our indoor technology adopters, can be categorized as *Late majority*. According to this seminal work, this type of consumer is characterized by being skeptical about innovation, having little opinion leadership, and being in contact with other consumers in *late majority* and *early majority*. This characterization seems consistent with our findings that these consumers adopt the subsidized technology but do not experience an acceleration effect. Regarding the outdoor water-efficient technologies, households performing landscape transformation and adopting weather-based controllers in our study can be categorized as *early majority* and *early adopters*. These consumers have the highest degree of opinion leadership among the other adopter categories and therefore are more likely to adopt other water-efficient technologies. Again, this is consistent with our findings that households receiving rebates for the adoption of outdoor technologies tend to invest significantly more in other technologies. All of this suggests that rebate programs to promote the adoption of water-efficient technologies may be more effective when the level of adoption is still low, such as for our outdoor technologies, instead of promoting more well-established indoor technologies.

As noted in Section 1, our dataset does not allow us to directly estimate the amount of water conservation achieved due to the rebate programs because we lack exact adoption dates. Thus, it is not possible to conduct benefit-cost or cost-effectiveness analyses for the rebate programs using only this data. In order to address this issue, we combine our results with the water conservation estimates from the *Water Short List* by Inskeep and Attari (2014) to draw policy conclusions. Because we reject for all rebate programs the null hypotheses of Total and Partial crowding-out (when considering Tot_WT and $NoSub\_WT$), we can say that the four programs generate additional water savings. According to Inskeep and Attari (2014), indoor technologies tend to achieve lower water savings compared to outdoor technologies. In particular, *Efficient washers* and *Low flow toilets* may reduce indoor water use by around 17% and 19%, respectively, whereas estimated outdoor water savings for *Landscape transformation* and *Weather-based controllers* are 20-100%[6] and 30%, respectively. Considering that average indoor and outdoor water use by Californian households are roughly the same, it is apparent that outdoor technologies are likely to generate larger water savings. Moreover, as seen above, rebates for outdoor technologies not only generate a direct additionality effect, but also an acceleration effect. Therefore, for both of these reasons, it is seems that outdoor rebate programs have greater potential water savings than indoor programs. To investigate relative cost-effectiveness for water agencies[7], we show in Table 7 the rebate amounts for each of the technologies considered. The amounts are relatively

[6]Water savings achieved by replacing turf grass with water-wise landscaping differs based on the proportion of lawn replaced.

[7] In order to analyze cost-effectiveness for the consumers, one would need to compute the level of water use saved due to the rebate programs, but also the percentage of the investment covered by the rebate program. Unfortunately, that information is not available in our data. Participant households receive the rebate after purchasing the qualifying device in the store they choose. There is a large number of qualifying devices for each of the technologies considered in this analysis, and therefore, the percentage of the cost covered varies depending on the device selected by the household and the store where it is purchased.

similar, with *Efficient washers* being the highest. Therefore, if households appropriately use each technology and achieve the estimated savings mentioned above, one could expect that rebates for outdoor technologies would also be the most cost-effective. However, further analysis would be needed to investigate these speculative claims.

Table 7: Rebate amount perceived by participant

	Rebate amount ($)
Efficient washers	$200
Low flow toilets	$150
Landscape transformation	$150[8]
Weather-based controllers	$150

6 Conclusions

This paper analyzes the effects of several residential rebate programs on the adoption of indoor and outdoor water-efficient technologies in a Southern California water district. To do so, we adapt a common approach in the R&D literature that allows us to address two research questions. First, we test whether each rebate program generates larger investment in water-efficient technologies that would not have occurred in the absence of the rebate. Second, we analyze whether each rebate program promotes additional private investments in the other technologies we observe.

Our results indicate that while rebates for indoor technologies increase adoption to levels that would not have occurred in the absence of the program, these rebates do not generate an acceleration effect. In the case of rebates for outdoor technologies, we observe both effects, although the acceleration effect is limited to additional private investment in outdoor technologies. That is, the impact of rebates for outdoor technologies seems to be greater. Furthermore, because the outdoor water-efficient technologies in our analysis are in early stages of adoption, rebates would be useful to further promote the diffusion of these technologies into additional households.

[8] Rebate participants obtain $3 per square foot of turf removed, with $150 being the mean rebate.

Moreover, while our database does not allow us to estimate the actual level of water savings caused by the rebate programs, we can use the *Water Short List* by Inskeep and Attari (2014) to conclude that rebates for the adoption of outdoor water-efficient technologies seem to generate larger direct water savings, and also indirect water savings due to the acceleration effect. Moreover, considering that the rebate amounts are almost identical across subsidized technologies, one could expect the rebates for outdoor technologies to be more cost-effective if households use them appropriately. However, additional research that directly analyzes the cost-effectiveness of rebate programs is needed to substantiate these claims. In the current context of increasing water scarcity and heightened budget austerity, such information could help policy makers design rebate programs that generate larger benefits on limited budgets.

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